Research Article

Evaluation of Using Genetic Algorithm and ArcGIS for Determining the Optimal-Time Path in the Optimization of Vehicle Routing Applications

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Transportation is regarded as one of the most important issues currently being researched; this issue needs the search for approaches or processes that might lessen many contemporary traffic concerns. Congestion, pollution, and accidents have escalated lately, negatively impacting urban environments, economic development, and citizens' lifestyles. The rise of illnesses and epidemics throughout the world, such as COVID-19, has created an urgent need to find the best way to save people's lives. The vehicle routing problem (VRP) is a well-known moniker for improving transportation systems and is regarded as one of the ancient and contemporary difficulties in route planning applications. One of the main tasks of VRP is serving many customers by determining the optimal route from an initial point to a destination on a real-time road map. The best route is not necessarily the shortest-distance route, but, in emergency cases, it is the route that takes the least fitness cost (time) and the fastest way to arrive. This paper aims to provide an adaptive genetic algorithm (GA) to determine the optimal time route, taking into account the factors that influence the vehicle arrival time and cause delays. In addition, the Network Analyst tool in ArcGIS is used to determine the optimal route using real-time map based on the user's preferences and suggest the best one. Experimental results indicate that the performance of GA is mainly determined by an efficient representation, evaluation of fitness function, and other factors such as population size and selection method.

1. Introduction

Transportation problems, which many countries have faced, have been considered vitally significant in the last few decades; these problems necessitate a search for new techniques or alternatives that could determine the shortest time routes between any two locations. The vehicle routing problem (VRP) appeared for the first time in 1959 [1] to reduce the total route cost on continuously updated road maps. Several situations, particularly emergencies, require developing such techniques because the shortest-distance path sometimes is insufficient to save valuable human lives; the shortest-time route is optimum.

Two distinct types of VRP have been extensively explored individually, while appearing to be the same or overlapping at times due to mutual interests in network-based optimization models and techniques. First, a dynamic VRP that deals with dynamic road networks is a well-known and extensively studied class. Several dynamic and changeable characteristics, including traffic flow level, unanticipated occurrences, and weather conditions, impact such networks. The second type of VRP is the timetabled or scheduled VRP, which is concerned with public transportation and services involving the conveyance of passengers, such as buses, and operates primarily on regular timetables and trip schedules for public use.

This paper proposes a newly developed GA applied on a weighted directed graph representing a real-time road network of the study area, Al-Salt city in Jordan. An integrated ArcGIS Network Analyst tool has been used to

visually establish the optimal time route from a source point to the destination and suggest potential routes based on user preferences.

GA consists of consecutive procedures that attempt to find the best solutions to problems when it is possible to define the criteria used to evaluate and estimate the best solutions.

The proposed GA finds the shortest-time route with fitness function, which calculates the time influenced by different factors. The fitness function uses static and dynamic parameters to calculate each path's fitness value. The fixed parameters tend to be almost constant through time as follows:

(1) Route distance: the distance is the essential criterion for the shortest path problem; GA uses the road length as weight in the directed graph for obtaining the best route.

(2) Easiness of driving: the safer and more comfortable route is also a driver preference criterion. The proposed GA should find a vehicle route that achieves the driver requests based on this criterion; furthermore, the determined solution should avoid influencing factors like traffic signals.

(3) Streets conditions: these include street type, width, street topology, and street regulations (e.g., allowed velocity limit); the street conditions can be collected using cameras, sensors, car navigation system, and geodatabase of the real-time map. The proposed technique obtains the above parameters from the geodatabase of Al-Salt downtown map.

The dynamic factors, such as residential density, are relatively variable throughout time (low, medium, and high density). Travel time reflects the time spent travelling by automobile, such as rush hour in the morning from 6 a.m. to 10 a.m. The residential density in a given region may be calculated using real-time map data and then updated on a regular basis utilizing cameras and sensors, particularly during peak hours.

2. Related Work

Several researchers have made a considerable effort to optimize transportation systems by improving and developing various algorithms to solve VRP problems in route planning systems. Figure 1 shows the most popular algorithms for determining the optimal route in VRP, and they are classified as follows.

2.1. Exact Algorithms. A comparative study has been conducted for different VRP algorithms to evaluate their effectiveness in real-time routing applications and simulate the performance of Dijkstra's algorithm (DA) among them [2]. Position parameter [3, 4] was added to DA using the global positioning system (GPS). Once GPS retrieves the current position, DA calculates the distance from the source to every node in the graph [5, 6].

The researchers in [7] improved the DA; moreover, they have examined the weaknesses of other shortest path algorithms. Dijkstra algorithm was also applied in public transport planning system for Bangkok Metropolitan Area for Buses as in [8], intelligent bus transportation system in Philippines [9], shortest-distance bus routes in Yangon city [10], and parking system in Malaysia [11]. Other research works [12, 13] used breadth-first traversal (BFT) to improve the efficiency of DA in the searching process for the best solution for VRP.

2.2. Heuristic Algorithms. A^* search algorithm has been studied and used to find the point-to-point shortest route using a weighted directed graph [14]. Another research [15] shows that the execution time of DA is lower than the A^* search algorithm when a large number of nodes are selected. A public transportation system of Yangon's downtown area applied the A^* approach in finding the shortest route [16]. The research in [17] has applied the branch-and-bound algorithm on the cost function $f(x)$, while the branch-and-cut algorithm was used in [18, 19] to solve the vehicle assignment problem and the two-echelon vehicle routing problem, respectively.

2.3. Metaheuristic Algorithms. GA is an evolutionary technique developed for the first time by Holland et al. in 1975 [20]. GA always begins with an initial population of randomly selected chromosomes; each chromosome represents a potential solution containing a combination of genes [21].

GA commonly uses one crossover and one mutation operator to solve the problem and determine a new optimal solution, but researchers in [11] defined one crossover and three mutation operators to find the optimal path. Depending on the experimental results, the algorithm was quick, prosperous, and stable and had a good convergence with high efficiency in determining the shortest emergency route [22]. Variable-length chromosomes with string type are proposed in [23].

When compared to other recent metaheuristics, GA offers a wide range of applications, including a vehicle routing problem (VRP) combining time frames [24–30] and a school bus routing issue [31–33]. A route guiding system used GA in a mobile application to determine the quickest driving time for Ankara's traffic network [34].

Several metaheuristic algorithms are also applied to solve VRP problem like Ant Colony Optimization (ACO) as in [35–38], Tabu Search in [39–43], and Particle Swarm Optimization (PSO) in [44]. Figure 1 summarizes the main three approaches, exact, heuristic, and metaheuristic algorithms, applied in VRP using real-time maps.

Many studies have demonstrated the effectiveness and importance of GIS in optimizing transportation systems and determining the most fitting routes for vehicles.

The ArcGIS Network Analyst tool has recently been used to optimize several route planning applications. The researchers in [45, 46] have used GIS Network Analyst to optimize the solid waste management field. In [47], the authors planned to provide information about tourist
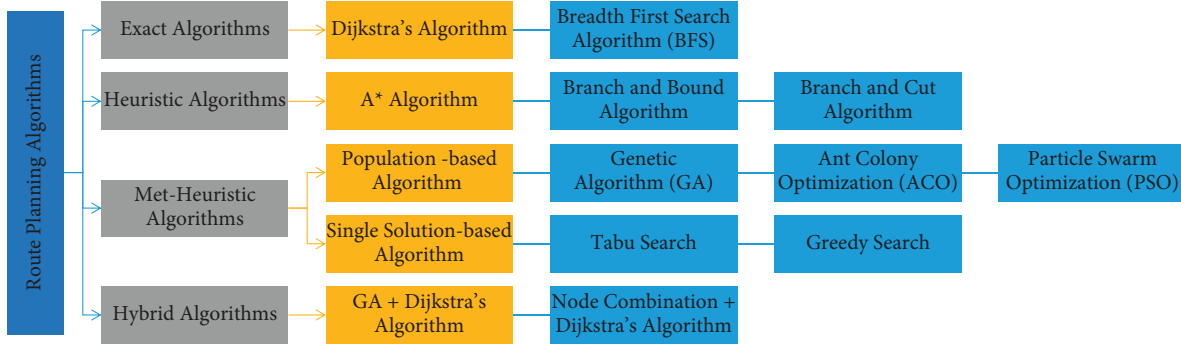
FIGURE 1: Classification of route planning algorithms.

attractions in Bandung and create a tourism-specific mass transit route. Based on a network-based spatial analysis of a GIS-based map, the study in [48] uses Dijkstra's algorithm to identify the shortest-distance route.

This study uses an integrated Network Analyst tool with a GA approach for vehicle routing optimization to determine a multiobjective optimal route based on user preferences. Generally, GA works well in problems with a huge solution space, long search times, and complex fitness functions. Furthermore, it performs well and gives better results when the function is discontinuous and noisy or has many local optimums. According to this study, GA becomes more complex when there are a considerable number of nodes in the real-time road network because unlimited-length chromosomes are created.

3. Study Area

Al-Salt city is one of the ancient and densely populated cities in Jordan. The city is located about 30 kilometers northwest of Amman, the capital city of Jordan, between longitude (35° 43′ 30″) east and latitude (32° 02′ 30″) north, at the height of 795 to 1,110 meters above sea level.

The study area represents road networks in the downtown of Al-Salt city; the greater municipality of Al-Salt provided the study with real-time maps and the road networks for the study area in cooperation with Al-Balqa' Applied University, which provided the study with the required equipment and tools used for data collection.

The streets in the city of Al-Salt represent 4% of Jordan's total streets, including secondary and main streets. According to the road classification law at the Ministry of Public Works, Table 1 shows the types and lengths of roads in Al-Salt city in 2018 [49].

The roads were classified according to the width of each road as follows:

  (i) Main road: the width of the road is 8 m or more.

 (ii) By road: the width of the road is 6 m up to less than 8 m.

(iii) Track road: the width of the road is 3 m up to 6 m.

Studying the road networks is one of the critical fields in transportation systems; it combines the spatial relation of the road networks with their characteristics then analyzes

TABLE 1: Classification for the main types of roads in study area.

Type of road	Distance (km)	Percentage (%)
Main road	216.31	28.40
By road (secondary)	415.62	54.66
Asphalt (track)	128.51	16.94
Total	760.44	100

them according to space. Figures 2 and 3 show satellite images of the study area with the associated digitized road networks.

4. Methodology

Photogrammetry refers to the process of measuring and interpreting images in order to extract data needed for geospatial applications, which is often acquired by satellites and airplanes.

The key tool in this case study is ArcGIS. It is an ESRI-developed geographic information system (GIS) for dealing with maps and geographical information. It provides a framework for making maps, assembling geographic data, evaluating mapped data, and integrating maps with geospatial databases in a variety of applications [50]. Figure 4 depicts the methods for producing the study map to be combined and used with GA to discover the best-time route.

4.1. GPS Field Survey to Get the Ground Control Points (GCPs). The next step is to take the GPS data and postprocess it by importing raw data (the data from the GPS receivers) and exporting the final local grid coordinates and other coordinates. It is composed of the points BAU, reference, az, bs, seha, sew, hassan, hesba, salalem, and fatma. Only two receivers were used to measure the entire network.

The local grid coordinates of the points BAU, reference, az, bs, seha, sew, hassan, hesba, salalem, and fatma are derived and known as UTM ZONE 36 North projection and WGS84 Ellipsoid. Figure 5 displays the local grid coordinates for the previous selected points.

4.2. Process the GPS Field Data by Leica SKI-Pro Software to Get Values of GCPs. Leica's SKI-Pro software includes a comprehensive set of programs for GPS surveying with
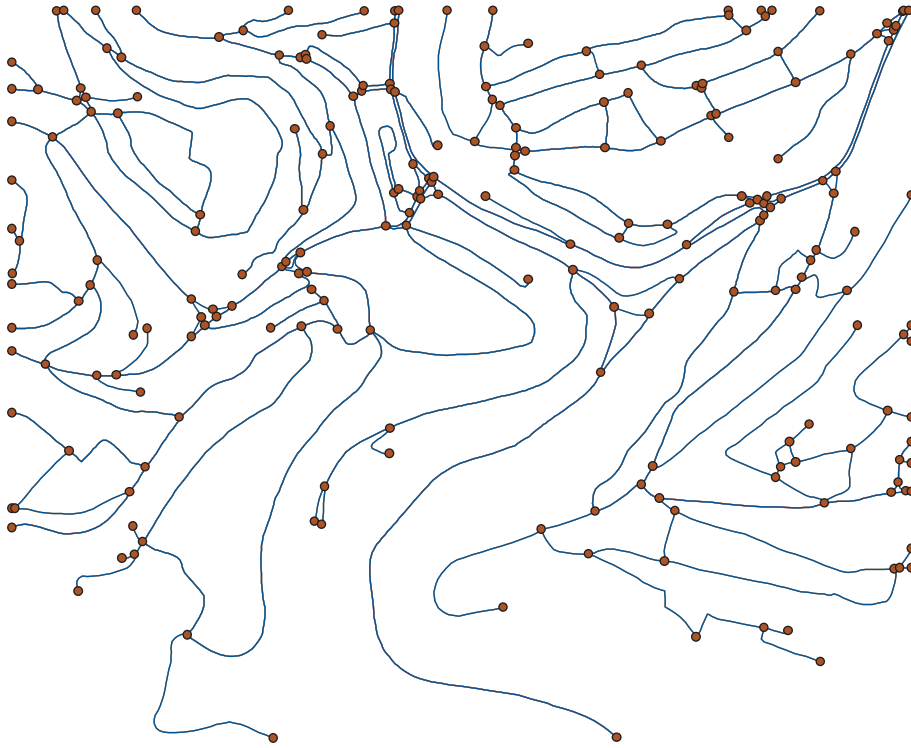
Figure 2: Real-time road networks of study area.

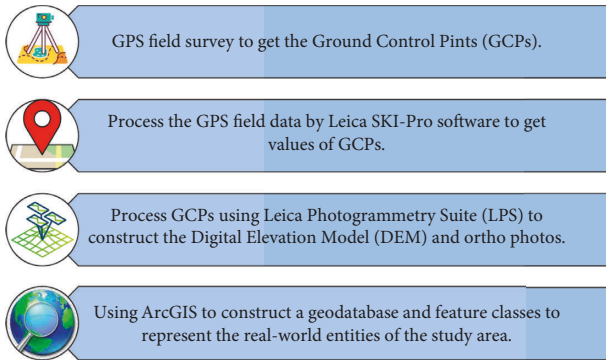Figure 3: Satellite aerial photo of study area.

Figure 4: Procedures of georeferencing the study area.

Figure 5: Local grid coordinates of the study area.

postprocessing capabilities and real-time support. In SKI-Pro, GPS data that belong together can be collected and stored as shown in Figure 6.

4.3. Process GCPs Using Leica Photogrammetry Suite (LPS) to Construct the Digital Elevation Model (DEM) and Orthophotos. In this study, Leica Photogrammetry Suite (LPS) is applied to find the overlap area between two images, also known as triangulation, by rectifying images to determine orthophoto as well as extracting DTMs and contour maps for use in ArcGIS. Figures 7 and 8 display the locations of GCPs and determine their type and usage.

4.4. Using ArcGIS to Construct a Geodatabase and Feature Classes to Represent the Real-World Entities of the Study Area. The process of digitizing GIS data is to convert scanned images or hard copies of geographic data into vector maps by tracing their features. It is one of the ways to ensure that real-world spatial data is accessible. The digitization process involves

capturing the underlying map features as coordinates, either as a point, line, or polygon. The task is accomplished by creating layers in ArcCatalog and then adding features to them in ArcMap. Several layers have been created in this stage for the study area in order to use them for retrieving the required spatial data by GA to calculate the optimal time route, as illustrated in Figure 9.

5. Proposed GA for Route Planning Systems

The most critical and challenging task for developing GA to this problem is how to encode a route in a weighted directed graph into a chromosome. This paper proposes a new GA for solving the shortest-time routing problem and determining the shortest-time route (optimal). Variable-length individuals (chromosomes) have been used; the genes in each chromosome represent nodes included in a path between a selected pair consisting of source (start) and destination (end) positions, and a priority-based encoding procedure is followed, which can probably represent all feasible routes in a graph.

5.1. Graph Design. In an implicit way, a road network can be represented as a directed graph $G = (V, E)$, where N is a set of vertices (nodes) and E is a set of edges (arcs). The ID of a node in the graph has given a unique positive integer value from $1, \ldots, N$, where N is the number of nodes as in Figure 10.

Each chromosome is created to represent a solution for the shortest-time routing problem, and it should not include duplicated nodes. Source and destination nodes are indicated by F and E, respectively, and each link (i, j) has associated with link connection indicator expressed by I_{ij}, which takes a part and plays an important role in chromosome production and encoding via providing connection information; this information describes whether the link from node i to node j is included in the routing path or not.

The connection information of the nodes with each other can be determined with an adjacency matrix as follows:

$$I_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ are connected (adjacent)}, \\ 0, & \text{otherwise}. \end{cases} \quad (1)$$

An adjacency matrix in Figure 11 is used to ensure the connectivity of the randomly selected pair of vertices; the length of the edge is considered as the weight of that edge in the graph. The adjacency matrix illustrates that all the diagonal elements of I_{ij} must equal zero, where the source and destination nodes are the same ($S = E$). The minimum potential value of the chromosome length is equal to the total number of nodes in the whole graph, because, in some worst cases, the shortest path may contain the total number of nodes. The gene length of a graph with N number of nodes is equal to N or more.

5.2. Chromosome Representation (Encoding). Chromosome length is variable, but it must not increase beyond the maximum feasible size, which, in the worst case,
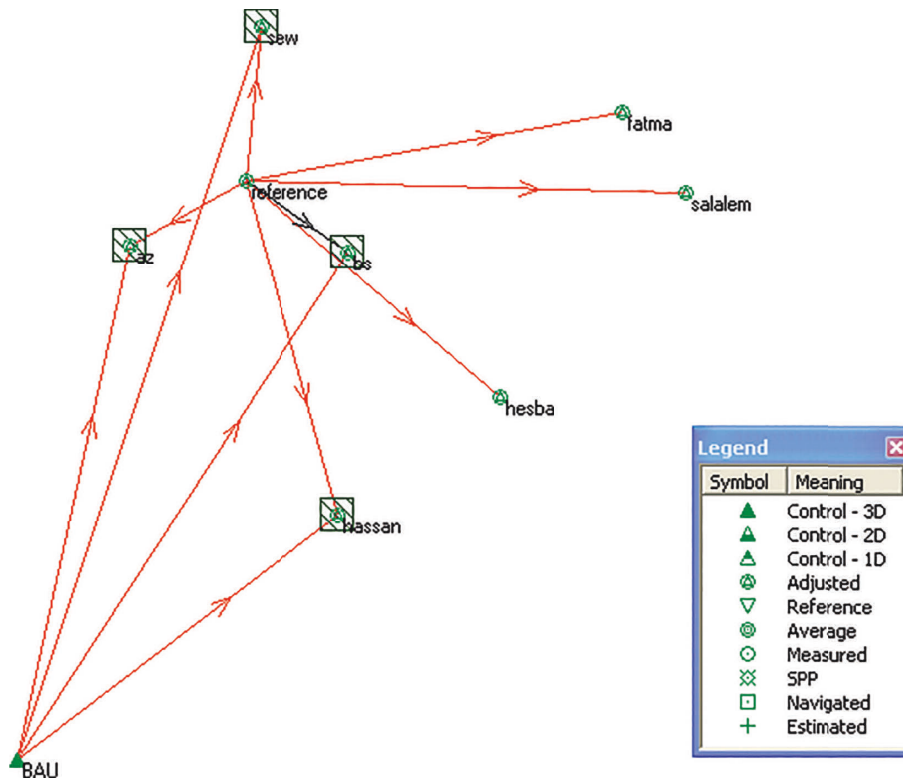
FIGURE 6: Distribution and adjustment of GCPs.

FIGURE 7: Location of GCPS on study map.

Point #	Point ID	>	Description	Type	Usage	Active	X Reference	Y Reference	Z Reference
1	1	>	az	Full	Control	X	757005.703	3547798.025	912.441
2	2		bs	Full	Control	X	757692.411	3547792.400	809.709
3	3		fatma	Full	Control	X	758540.116	3548253.885	920.186
4	4		hassan	Full	Control	X	757677.553	3546963.794	740.262
5	5		hesba	Full	Control	X	758178.094	3547347.288	767.178
6	6		reference	Full	Control	X	757362.178	3548008.234	839.290
7	8		salalem	Full	Control	X	758746.200	3548003.621	849.996
8	9		seha	Full	Control	X	757707.629	3548094.642	822.302

FIGURE 8: The type and usage of GCPs.

is the total number of nodes in the network since the chromosome length does not require more than the total number of nodes in order to create a routing path. Figure 12 shows the chromosome representation where the genes are selected randomly from source node 1 to destination node 4 based on the topological information database of the network; each chromosome should indicate a feasible route for the proposed GA.
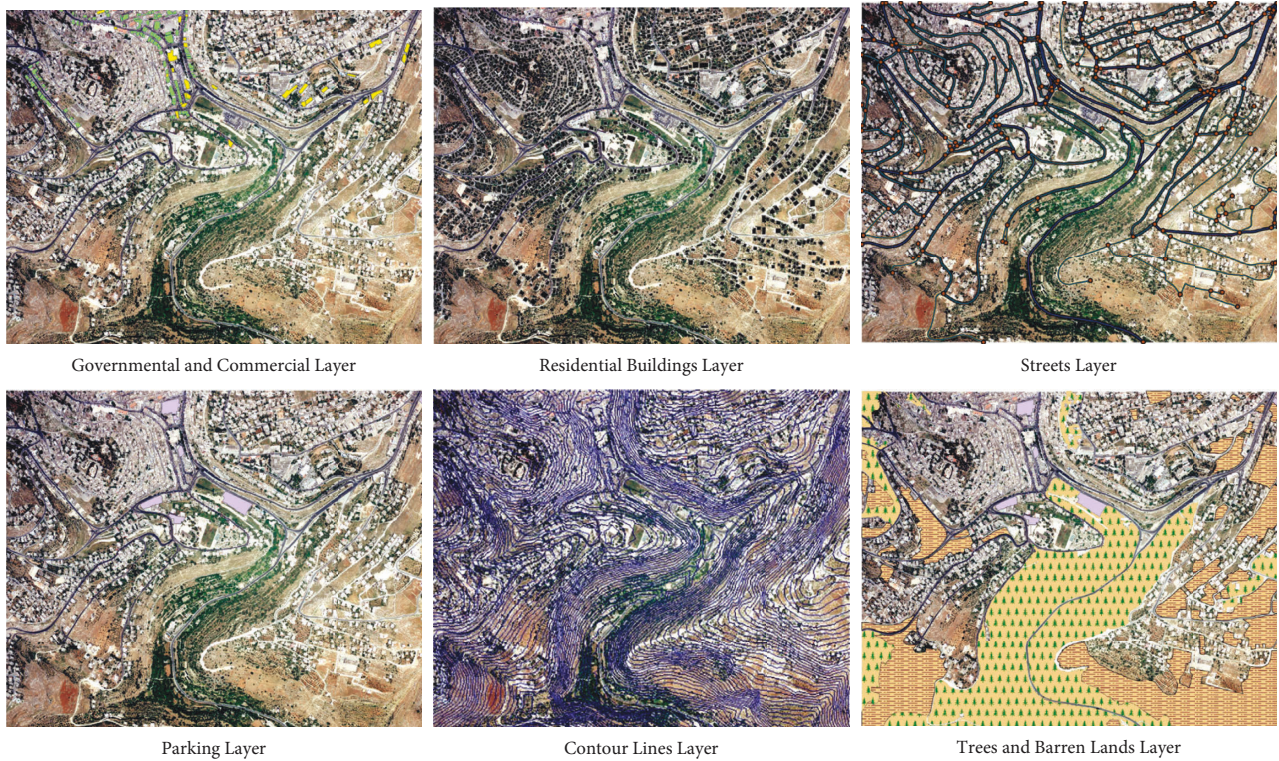
Governmental and Commercial Layer

Residential Buildings Layer

Streets Layer

Parking Layer

Contour Lines Layer

Trees and Barren Lands Layer

FIGURE 9: Digitized layers view concerning the rectified orthophoto.
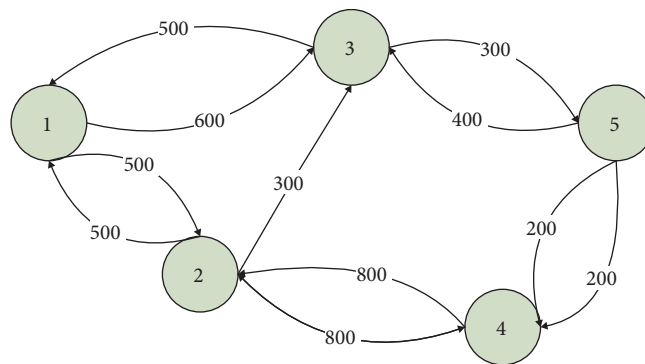
FIGURE 10: Directed graph for road network.

		N1	N2	N3	N4	N5
		1	2	3	4	5
N1	1	0	1	1	0	0
N2	2	1	0	1	1	0
N3	3	1	0	0	0	1
N4	4	0	1	0	0	1
N5	5	0	0	1	1	0

FIGURE 11: Adjacency matrix for road networks.
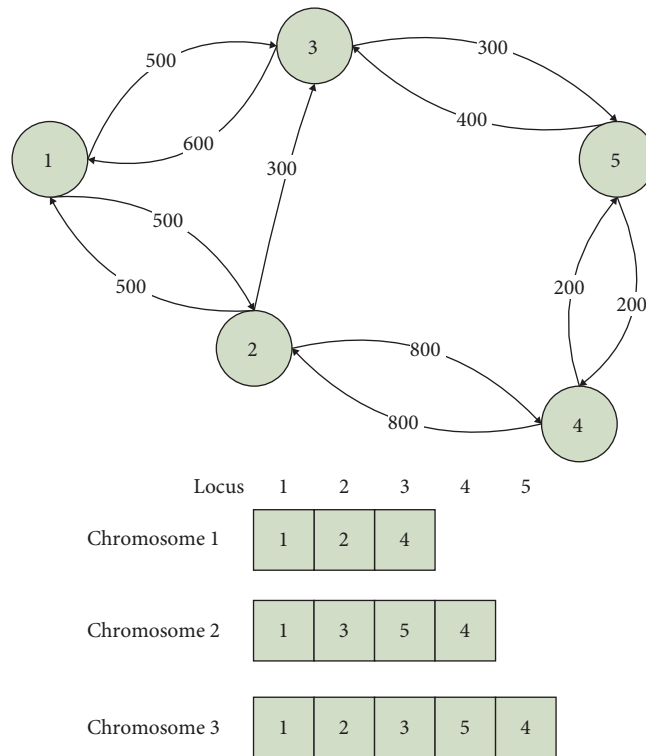
FIGURE 12: Chromosome representation procedure.

TABLE 2: Attributes table for road network segments.

Segment ID	Segment description (S, E)	Distance (m)	Allowable velocity limits (km/h)
S1	(1, 2)	500	60
S2	(2, 1)	500	60
S3	(1, 3)	500	60
S4	(3, 1)	600	60
S5	(3, 5)	300	40
S6	(5, 3)	400	40
S7	(4, 5)	200	40
S8	(5, 4)	200	40
S9	(2, 4)	800	40
S10	(4, 2)	800	40
S11	(2, 3)	300	60

5.3. Initial Population. The initial population consists of chromosomes (individuals), the lengths of which are variable. The first gene of each chromosome is the first node (S) and the last gene is the target node (E); if the path is between S, a new gene is produced; typically, all the chromosomes in the first generation are produced by this approach.

The large population is practically useful, but it requires unnecessary costs in both capacity and time. As expected, choosing a sufficient population size is critical for efficiency demands; for that reason, many researchers used the heuristic approaches for producing the chromosome for the initial population instead of the random method.

5.4. Fitness Function. Table 2 contains the cost attributes or parameters used in determining the fitness value for each segment of the road path and affects the result obtained.

Based on these criteria, the fitness cost for the candidate road pathways (chromosomes) from source node 1 to destination node 4 could be computed, and the optimum option with the least driving time would be chosen. Figure 13 depicts an actual value for each route in the research area's road network. Equations (2) to (7) define the fitness function of the GA while taking into account all of the associated parameters as follows:

FIGURE 13: Attribute table of streets layer in ArcMap.

$$T1_{ij} = \sum_{n=i}^{j} \left(\frac{\text{dis}_{ij}}{V_{ij}} \right). \qquad (2)$$

Fij is the cost value from i to j, where $i \neq j$.

$$T1_{ij} = \sum_{n=i}^{j} \left(\frac{2\text{dis}_{ij}}{V_{ij} - VRij} \right) \text{in rush hours}, \qquad (3)$$

where dis_{ij} is the length of segment between i and j and V_{ij} represents the allowable velocity limits between i and j.

Then,

$$Dy = \frac{\sum L}{A} \times 100, \qquad (4)$$

$$T2_{ij} = \sum_{n=i}^{j} \left(\frac{Dy}{V_{ij}} \right), \qquad (5)$$

$$T3_{ij} = T1_{ij\_}T2_{ij}, \qquad (6)$$

where

$$T4_{ij} = T3_{ij} - (NOTL * 0.5)(\text{minimum}), \qquad (7)$$

$$F_{ij} = \sum_{n=i}^{j} T_{ij}. \qquad (8)$$

T_{ij} is the time required to travel between i and j. Dy is the density of the roads network. $\sum L$ is the total length of the network roads. A is the area of the study region (square kilometer). NOTL is the number of traffic light signals. VR_{ij} is the estimated vehicle's speed in rush hours.

5.5. Selection and Crossover Procedures.

The tournament selection method is the type of selection used for the proposed GA, two individuals are selected, and the more appropriate individual is chosen compared to the fitness of the other chromosomes in the population, but the corresponding individual should not be selected twice as a parent in the population.

In 1983, Birndlerproposed a tournament selection technique in which individuals, in pairs, were selected according to their fitness values from a stochastic roulette wheel. Selection of the individuals with the highest fitness values leads to the next generation.

The crossover between the two most fitting parents chosen by the selection increases the probability of generating offspring having robust characteristics [51]. The arithmetic crossover is used in this case as follows:

$$X_i = \delta . X_i^1 + (1 - \delta) . X_i^2, \qquad (9)$$

where $\delta \varepsilon (0, 1)$.

According to the previous equation, the new offspring generated by the arithmetic crossover are

$$\begin{aligned} P_i &= \delta . X_{i+(1-\delta)Y_i}, \\ q_i &= \delta . X_{i+(1-\delta)Y_i}. \end{aligned} \qquad (10)$$

Figure 14 shows an illustrative example of the proposed crossover procedure.

5.6. Mutation Procedure.

Mutation procedure leads to a bit of increment in the probability of producing the infeasible chromosomes; it keeps the diversity in the population
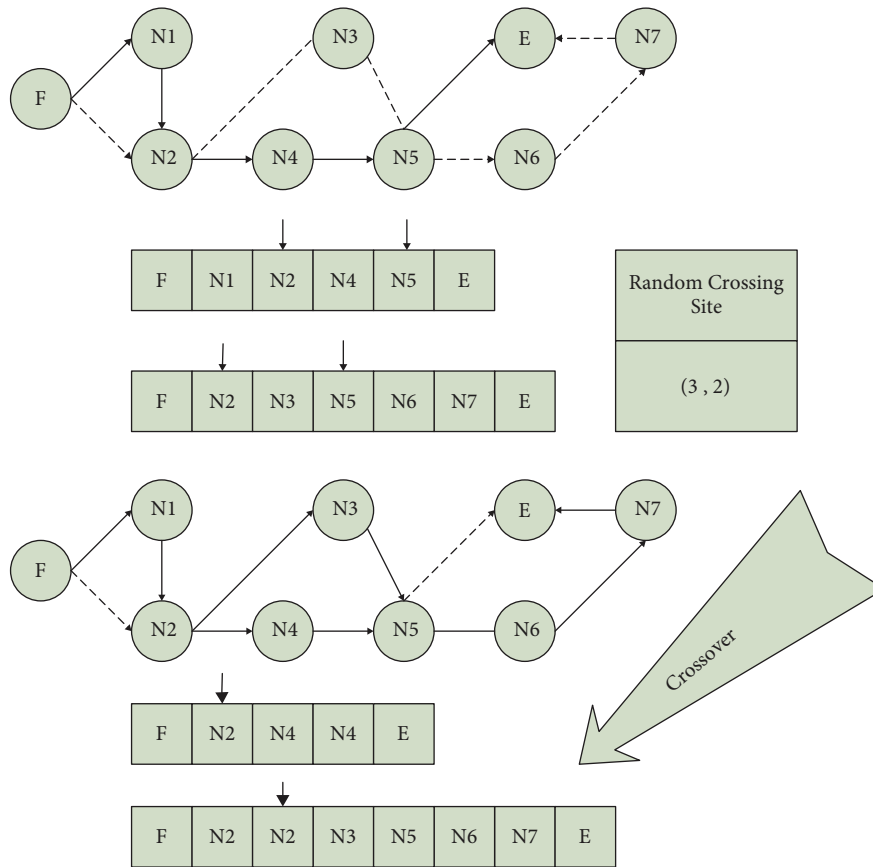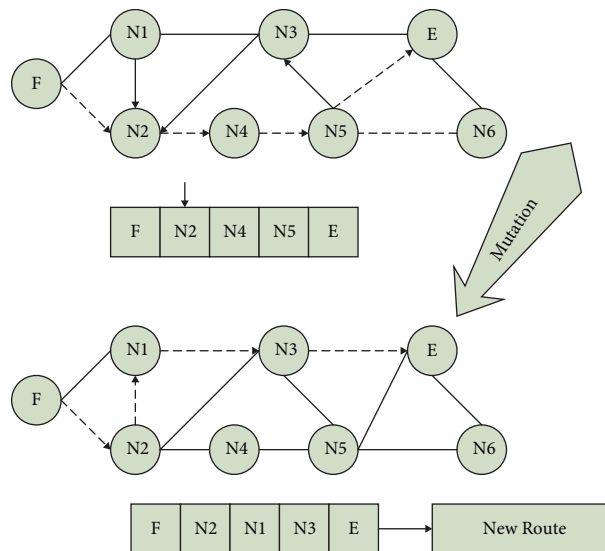
FIGURE 14: Crossover procedure.

FIGURE 15: Mutation procedure.

solutions. Figure 15 illustrates a comprehensive description for the proposed mutation procedure in GA.

5.7. Reorganizing (Repairing) Function. GA is developed based on ideas inspired by evolutionary mechanisms, where successive generations of solutions become more and more

efficient until an optimal or nearly optimal set of alternatives are reached.

Loops in the shortest-time route routing issue can be produced during the crossover and mutation procedures, resulting in infeasible chromosomes. There are two primary approaches to dealing with infeasible chromosomes. The first is to eliminate them, and the second is to
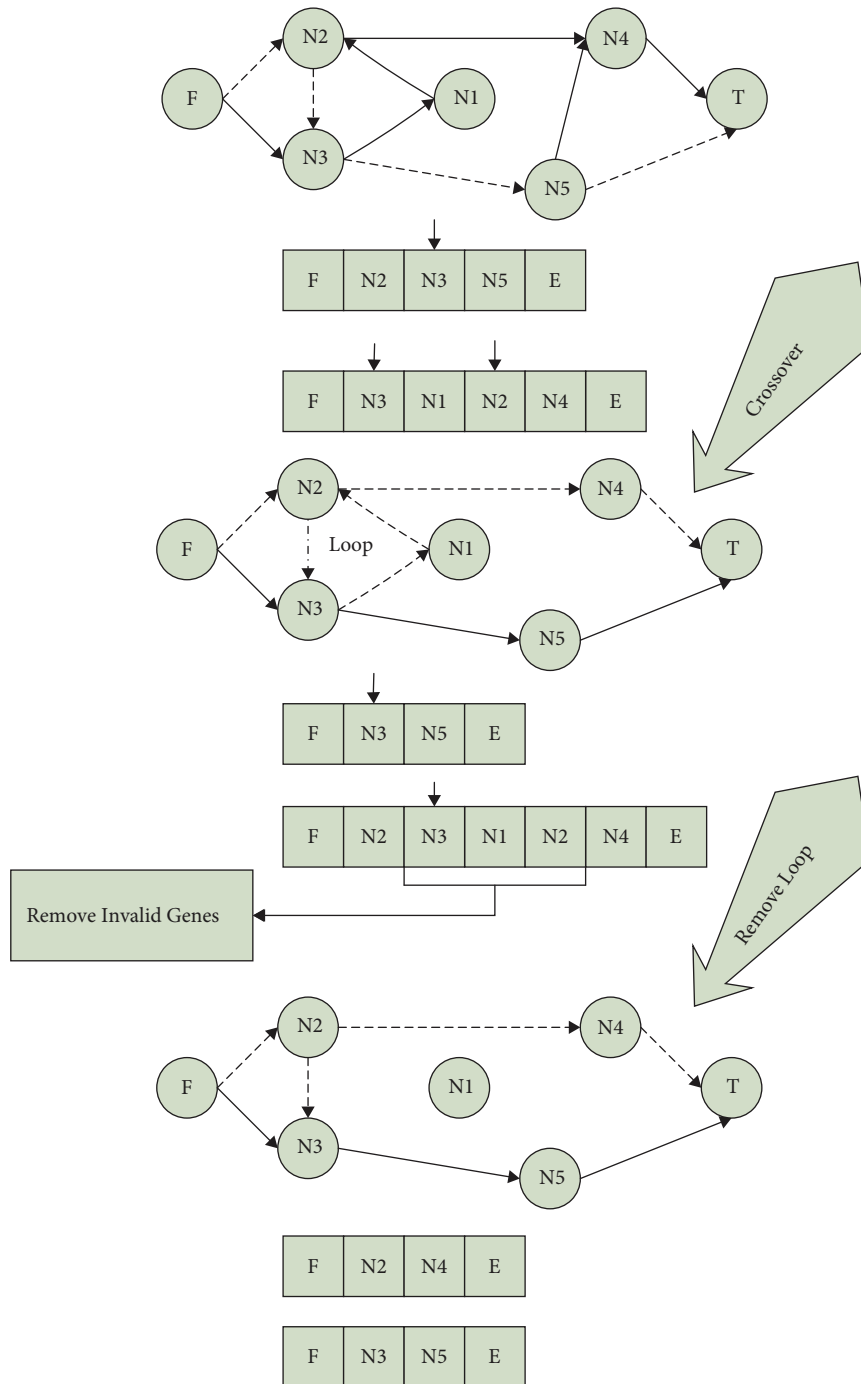
Figure 16: Repair procedure.

reorganize a chromosome with a repair function. The first is to apply a penalty, and the second is to reorganize a chromosome by removing and deleting the loop; in this work, the rearranging function is utilized to detect and eliminate the loops without incurring any additional capacity or time expenses. Figure 16 shows a description of the proposed reorganizing function with an example.

Algorithm 1 displays a pseudocode showing how the algorithm finds the minimum travel time route for the provided graph from start node to the end node.

6. Results and Findings

The road network in this study consists of 226 nodes (junctions) and 280 edges (segments), and each route has several interconnected edges. Determining the size of the initial population is crucial and influential in the effectiveness of the algorithm's performance. The initial population size tends to increase exponentially with the size of the road network due to an increase in chromosome length.

The quality of each chromosome in the population must be calculated accurately using efficient fitness

```
(1)      ►Input: Graph (V, E)
(2)        fNode/ ∗ initial node in the route */
(3)          dNode/ ∗ destination node */
(4)      ►Output: Ch[]/*array of Genes represents the optimal time route */
(5)        Define: Adj [][]/* 0, 1 Check nodes adjacency in the graph */
(6)        Ch [0] ← fNode
(7)          Pz ← Population size
(8)          Cr ← Crossover rate
(9)          Mr ← Mutatino rate
(10)           for each i, j where j = PZ
(11)         Create_Chromosome (fNode, dNode)
(12)           F ← Calculate Fitness Value for each chromosome
(13)             End for
(14)        Count ← 0
(15)        Gen ← 1
(16)          While Count ≤ 10 do
(17)        Ch1, Ch2 ← RouletteWheel _Selection ()
(18)        Ch1*,Ch2* ← Crossover (Ch1, Ch2)
(19)          Ch3 ← Mutation (Ch1*)
(20)          Ch4 ← Mutation (Ch2*)
(21)          F1 ← Fitness Value for the first chromosome
(22)          F2 ← Fitness Value for the second chromosome
(23)          Fm ← Minimum Value of fitness function
(24)            If Gen > 1 && Fm (Gen-1) = = Fm (Gen-2)
(25)          Count ++
(26)        if count > 10
(27)          Break
(28)        else
(29)        count = 0
(30)        End If
(31)        End while
(32)        Gen ++
(33)        Go to 17
```

ALGORITHM 1: Pseudocode for GA implementation.

TABLE 3: The calculated fitness value with allowable velocity limit for three chromosomes (routes).

Route	Segment (S, E)	Length (m)	Vehicle speed			
			40 km/h	60 km/h	90 km/h	120 km/h
	(1, 2)	500	0.750	0.50	0.333	0.250
Route 1	(2, 3)	300	0.450	0.30	0.200	0.150
	(3, 5)	300	0.450	0.30	0.200	0.150
	(5, 4)	200	0.300	0.20	0.133	0.100
Total (minutes)			1.950	1.30	0.867	0.650
Route 2	(1, 2)	500	0.750	0.50	0.333	0.250
	(2, 4)	800	1.200	0.80	0.533	0.400
Total (minutes)			1.950	1.30	0.867	0.650
	(1, 3)	500	0.750	0.50	0.333	0.250
Route 3	(3, 5)	300	0.450	0.30	0.200	0.150
	(5, 4)	200	0.300	0.20	0.133	0.100
Total (minutes)			1.500	1.00	0.667	0.500

function. Based on a geodatabase of the study area map, a multiobjective fitness function was used in GA to estimate the minimum vehicle arrival time. In this section, the fitness value is calculated for each factor separately in order to illustrate their influence on the estimated time.
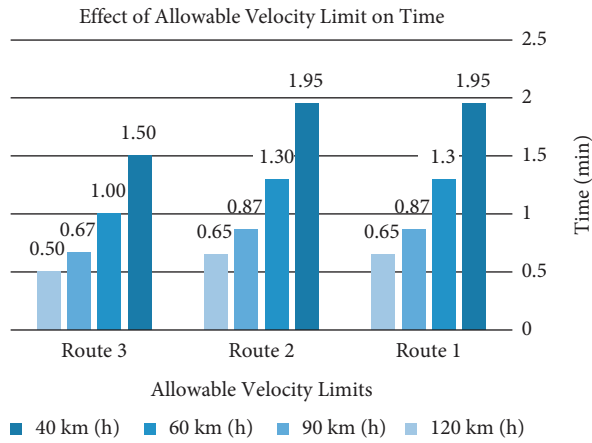
Effect of Allowable Velocity Limit on Time

Figure 17: The effect of the vehicle speed on the expected arrival time.
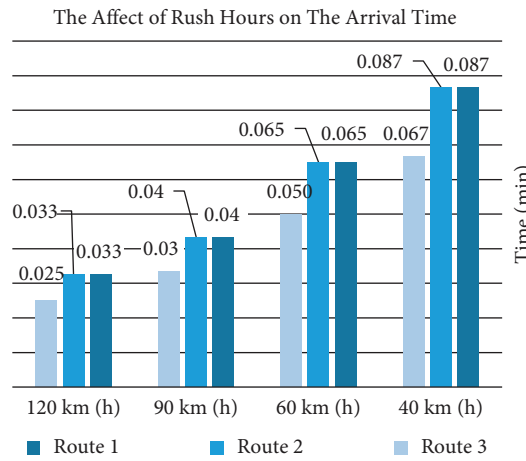
The Affect of Rush Hours on The Arrival Time

Figure 18: The effect of the rush hours on the expected arrival time.
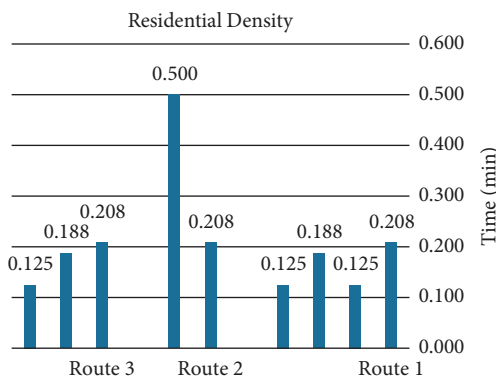
Residential Density

Figure 19: The effect of residential density of study area on the expected arrival time.

Table 3 shows the calculated fitness value for three chromosomes for the route from node 1 to node 4, considering the allowable velocity limit in measuring the value.

Figure 17 illustrates the effect of allowable velocity limits on the arrival time from node 1 to node 4 for three separate routes. As a result, the shortest-time route is not necessarily the shortest-distance one. The vehicle speed on the road, which is determined according to street condition (e.g., street type), has a significant effect on the time needed to arrive.

During peak hours, traffic congestion causes the creation of automobile lines, which decreases the speed of cars and delays their arrival at their destinations. Despite the fact that vehicle deceleration in real-world conditions is not exactly uniform, the delay for a specific vehicle may be estimated
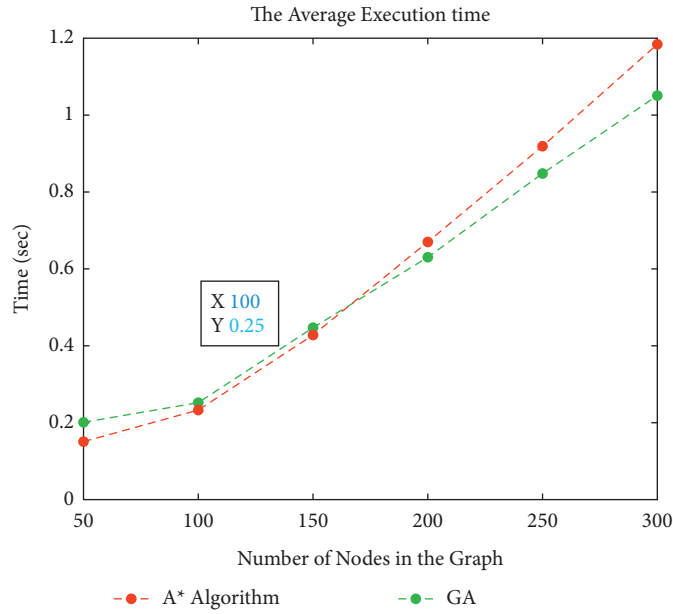
FIGURE 20: Execution time for A* algorithm and proposed GA.

TABLE 4: The calculated fitness value in rush hours for three chromosomes (routes).

| Route	Segment description (S, E)	Segment length (m)	Allowable velocity limit	Res. density	Time in rush hours (km/h)			
					40	60	90	120
	(1, 2)	500	60	0.208	0.033	0.025	0.017	0.013
Route 1	(2, 3)	300	60	0.125	0.020	0.015	0.010	0.008
	(3, 5)	300	40	0.188	0.020	0.015	0.010	0.008
	(5, 4)	200	40	0.125	0.013	0.010	0.007	0.005
Total (minutes)				0.646	0.087	0.065	0.04	0.033
Route 2	(1, 2)	500	60	0.208	0.033	0.025	0.017	0.013
	(2, 4)	800	40	0.500	0.053	0.040	0.027	0.020
Total (minutes)				0.708	0.087	0.065	0.04	0.033
	(1, 3)	500	60	0.208	0.033	0.025	0.017	0.013
Route 3	(3, 5)	300	40	0.188	0.020	0.015	0.010	0.008
	(5, 4)	200	40	0.125	0.013	0.010	0.007	0.005
Total (minutes)				0.521	0.067	0.050	0.03	0.025

(a)

(b)
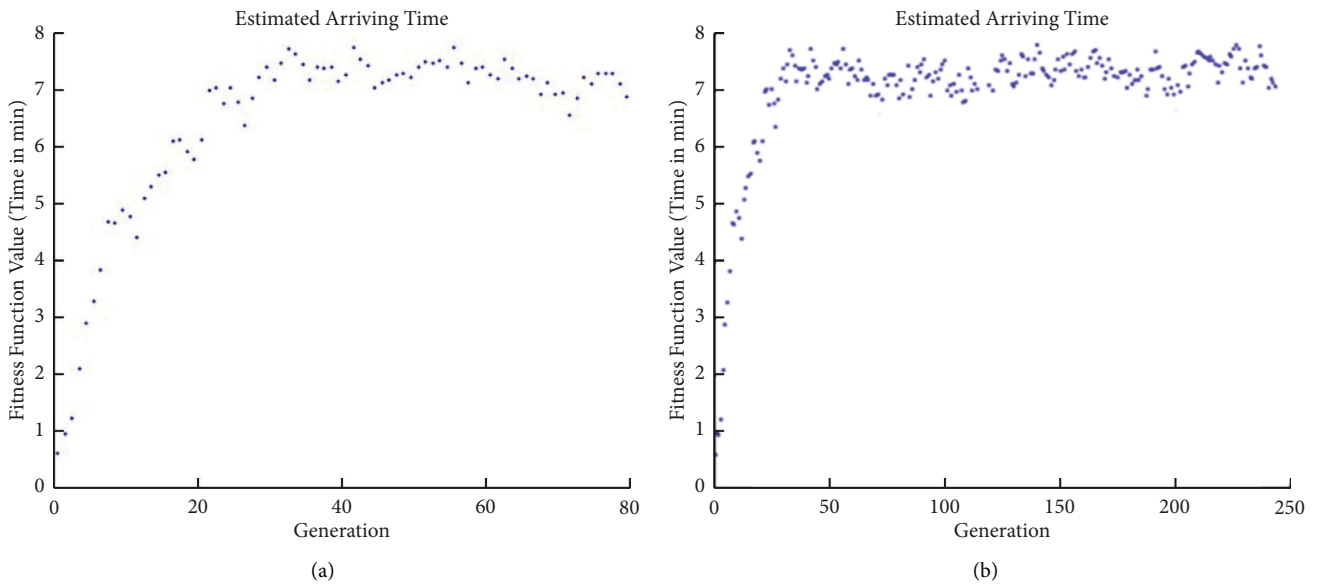
FIGURE 21: (a): Estimated time over 80 generations. (b) Estimated optimal time over 250 generations.

FIGURE 22: The first route from source to destination.

FIGURE 23: The first route from source to destination.

using fundamental dynamics equations. Because cars gradually slow down, this assumption should result in a somewhat realistic estimate of the time delay. Figure 11 depicts the effect of driving during rush hour on arrival time.

Figures 18 and 19 illustrate how deceleration of the vehicle during rush hours and the residential density affect the time needed to arrive, which are considered as important parameters in calculating each chromosome's fitness value in the proposed GA.

In order to emphasize the effectiveness of the genetic algorithm compared to heuristic algorithms such as the A* algorithm, a comparison was conducted according to the execution time required to determine the optimal solution as shown in Figure 20. Python is used to implement the algorithm, and the GA solver evaluates GA using MATLAB.
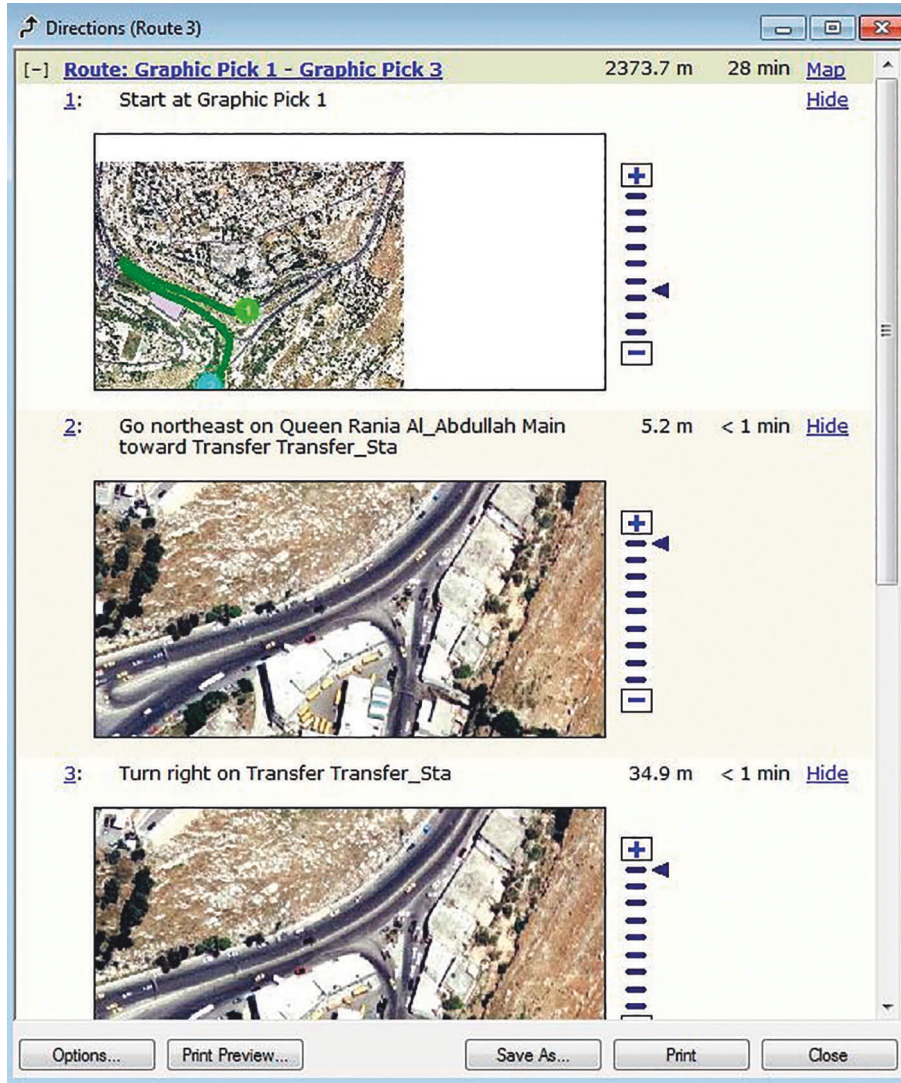
Figure 24: The shortest-time route for multiple locations.
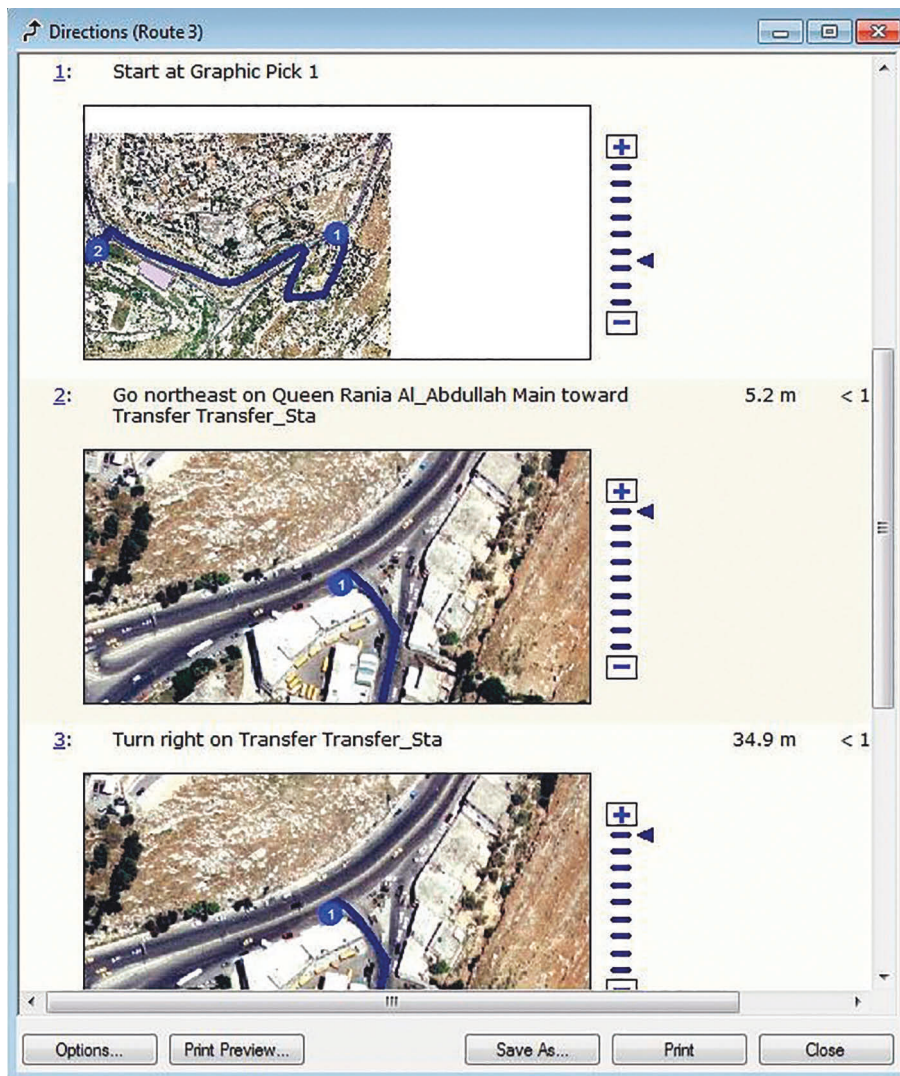
(a)

Figure 25: Continued.

(b)

Figure 25: Route directions window.

Table 4 shows the calculated time for three routes during rush hour, along with the residential density for each segment of the route.

The simulation results of GA using GA solver indicate that the proposed GA determines the optimal time route starting from 30 generations and performs effectively over more than 200 generations up to 250, as illustrated in Figures 21(a) and 21(b).

Based on various factors that affect the arrival time, the experimental results show multiple routes from the source to the destination. Figures 22 and 23 illustrate the shortest-time path obtained with multiobjective calculated time between two locations using GA. The results indicate that GA can be used effectively to design the route planning system that computes the optimal arriving time based on spatial database within dynamic traffic information.

The Network Analyst tool can also obtain the optimal route for multiple locations. It can estimate the best route between the source and destination, passing through specific locations, as shown in Figure 24.

Using ArcGIS integrated with GA, the Network Analyst tool can also provide the driver with other services besides obtaining the optimal-time route and selecting a specific route based on the driver's preferences. Furthermore, the application displays turn-by-turn directions for the preferred route with details that include the estimated distance and time for that route, as shown in Figures 25 and 26, respectively.

FIGURE 26: Estimated time and calculated distance.

7. Conclusion

When the problem space includes a huge number of solutions and searching takes a long time, GA might be a useful alternative. To find the optimal route, a modified GA with population initialization, crossover, mutation, and repair functions is used. GA effectively obtained the shortest-time route with variable-length chromosomes based on several criteria (e.g., distance, speed limit, residential density, traffic signals, and rush hour) over 30 generations and remained near the optimum for 200 generations. By comparing the A^* algorithm with the adaptive GA, it was found that, under increasing node density in spatial road networks, the proposed GA took the least execution time to find the optimal solution. Using ArcGIS to develop the Network Analyst tool helps users determine the shortest-distance route and simultaneously the shortest-time routes based on the user's impedance. GA will eventually be able to work perfectly with other heuristic algorithms, such as A^* and Dijkstra's algorithm, in a wide range of multiobjective optimization techniques in order to maximize its effectiveness in determining the best or near optimum solution.

Data Availability

The data used to support the findings of this study are available from the author upon request (si2784@putra.unisza.edu.my).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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